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Real-Time AI-Driven Stress Detection in Police Interrogations: Bridging Ethical Standards with Advanced Facial Recognition

Aravind H[1], Jogimol Joseph[2]

[1]Department of Computer Applications, Musaliar College of Engineering & Technology, Pathanamthitta, Kerala, India
Email: *aravindharikumar234[at]gmail.com*

[2]Professor, Department of Computer Applications, Musaliar College of Engineering & Technology, Pathanamthitta, Kerala, India

Abstract: ***This project presents a cutting-edge, real-time facial recognition system to evaluate stress levels during police interrogations. By utilizing advances in artificial intelligence and computer vision, the system identifies subtle facial expressions and physiological indicators such as micro expressions, eye activity, and pupil changes to monitor stress responses as they occur. Its main goal is to support law enforcement with objective, data-driven insights that can help pinpoint potential suspects and optimize interrogation efficiency. Through the integration of deep learning algorithms and motion tracking techniques, the system produces accurate stress metrics, which are visually represented through an intuitive interface. Ethical standards, including data privacy and algorithmic fairness, are integral to the system's design, ensuring equitable performance across various demographic groups. Although primarily focused on improving investigative methods, the technology also holds promise in other areas such as mental health assessment, mediation, and employee well-being monitoring. While there are ongoing challenges in refining precision and safeguarding personal data, the project aspires to transform investigative practices by merging AI-based analysis with strong ethical and scientific foundations.***

Keywords: Stress detection, real time monitoring, facial expression, workplace assessment

1. Introduction

This project focuses on harnessing advanced AI and computer vision technologies to create a real-time facial recognition system that analyses stress levels during police interrogations. The system is designed to detect facial expressions and physiological cues, such as eye movements and pupil dilation, providing an objective assessment of stress responses. By offering immediate, data-driven insights, this innovative solution aims to assist law enforcement in identifying potential suspects and improving investigative efficiency. Ethical considerations, including the prevention of biases and compliance with privacy standards, are integral to the project's implementation, ensuring fairness and reliability. The development of this system represents a significant step forward in integrating AI-driven tools into law enforcement practices while prioritizing scientific rigor and ethical integrity.

2. Related Works

Park H, et al. (2023) proposed an integrated model that fuses facial recognition and behavioural biometrics to enhance suspect identification in security contexts. The model depends on large-scale training data to ensure high accuracy across scenarios. However, its implementation may be resource- intensive and context-dependent [1].

Saha P, et al. (2020) examined the use of AI technologies in policing for crime prevention, presenting a case study highlighting real-world applications. While effective in proactive law enforcement, the study raised critical ethical concerns regarding the potential misuse of AI and surveillance overreach [2].

Dwork C & Roth A (2017) outlined the theoretical basis for differential privacy, offering privacy-preserving strategies essential for ethical AI surveillance deployment. Despite their value in protecting individual rights, these techniques may compromise model accuracy and operational effectiveness [3].

Brown J & White C (2016) developed a system for real-time behavioural monitoring within detention settings to identify security threats. Though the approach allows for continuous observation, it demands significant computational resources and extensive training data [4].

McDuff D, et al. (2013) introduced a deep learning-based method for measuring stress through facial and physiological indicators. While the technique proved effective, real-time implementation may require powerful computing hardware to process inputs efficiently [5].

Gupta S & Sharma A (2011) integrated AI with law enforcement databases to automate suspect detection. Their system demonstrated potential in identifying high-risk individuals but relied heavily on the completeness and accuracy of existing police records [6].

Zhao L & Xu K (2010) utilized deep learning to detect anomalous behaviour in surveillance footage, aiming to flag criminal intent. Despite its innovative approach, the system showed vulnerability to false positives caused by innocuous deviations [7].

Li S, et al. (2009) applied deep residual networks to improve facial micro-expression recognition for deception detection. While enhancing detection precision, the model required substantial computing power and precise tuning [8].

Haag A, et al. (2008) explored emotion recognition through biosensors, presenting a novel direction for stress detection. Although the approach showed promise, its dependency on wearable biosensors posed challenges for real-time law enforcement use [9].

Wang T, et al. (2007) proposed machine learning techniques for predicting crime-prone behaviour patterns. However, the system's reliance on potentially biased datasets raised concerns about fairness and profiling accuracy [10].

Jain A & Ross A (2005) reviewed behavioural biometric methods in forensic investigations, focusing on identifying individuals through movement patterns. Yet, natural variation in human behaviour complicated consistent accuracy [11].

Sanchez-Reillo R, et al. (2003) developed a deep learning-based system to detect stress through facial expressions during interrogations. However, stress cues could stem from factors unrelated to guilt, reducing the system's reliability [12].

Kollias D, et al. (2003) presented a convolutional neural network approach for detecting stress and fear as potential indicators of deceptive behaviour. The model's success was dependent on access to well-labelled, comprehensive datasets [13].

Viola P & Jones M (2001) introduced a robust, real-time face detection algorithm vital for suspect tracking systems. While fast and effective under ideal conditions, the method struggled with occluded or low-quality facial images [14].

Ekman P (1999) explored the correlation between facial expressions and emotional states, laying a foundation for psychological profiling in suspect interrogation. Though influential, the study lacked integration with contemporary AI- based stress detection tools [15].

3. Outlined Method

The methodology delineates the framework for designing and implementing a reliable and responsive fire detection system using the HSV colour model and the Gaussian Mixture Model (GMM). This system enables real-time fire detection by analysing video input, identifying fire-specific characteristics such as flame colour and motion, and issuing alerts with minimal false positives. The method comprises five key phases as detailed below:

a) Requirement Gathering and Analysis

The requirement gathering and analysis phase is essential for understanding the functional, technical, and user-centric needs of the proposed AI-based stress detection system. This phase involves identifying the inputs, outputs, user expectations, system behaviour, and constraints to ensure that the final implementation aligns with law enforcement objectives while maintaining usability, accuracy, and ethical standards.

b) System design

The design phase focuses on creating a system architecture that integrates face detection, feature extraction, and stress assessment. Face detection will be achieved using computer vision algorithms like OpenCV, Dlib, or deep learning-based models such as MTCNN to accurately detect faces in real time. Feature extraction will leverage models like Open Face to capture key facial expressions, eye movements, and pupil dilation, all of which are critical indicators of stress. The system will use a stress scoring algorithm built on deep learning models, such as CNNs or LSTMs, to analyse these features and assign a stress score based on recognized patterns of stress. For the user interface, a simple and intuitive dashboard will be developed, allowing law enforcement officers to view real-time data, including stress scores, facial expressions, and key physiological cues. Ethical considerations will be a priority, ensuring privacy through encryption, anonymization, and compliance with privacy regulations such as GDPR or CCPA.

c) Development

In the development phase, the focus will be on training the system to accurately detect stress-related facial expressions and physiological cues. Datasets like AffectNet, KDEF, and FER2013 will be used to train emotion detection and stress recognition models. These models will be trained using deep learning frameworks like TensorFlow or PyTorch. Real-time processing will be implemented to ensure that stress scores are calculated instantly from live video feeds. The system will integrate facial recognition, emotion detection, and stress scoring in a seamless manner, allowing law enforcement officers to monitor stress levels during interrogations. A critical part of the development will also be ensuring the system meets privacy and security standards by implementing encryption and anonymization techniques to protect the data.

d) Testing

The testing phase will begin with unit testing, where individual components, such as facial recognition accuracy and stress detection, will be verified for functionality. Integration testing will follow to ensure the smooth interaction between the video input, real-time analysis models, and the user interface. System testing will be conducted to ensure the system can handle various environments, such as different lighting conditions and camera angles. User Acceptance Testing (UAT) will involve collaboration with law enforcement officers to gather feedback on the usability of the system and its effectiveness in real-world interrogation scenarios. Additionally, ethical and bias testing will be conducted to verify that the system does not discriminate based on race, gender, or age, and that it accurately reflects stress levels across diverse populations.

e) Deployment

During the deployment phase, the system will be set up either on a cloud platform or on-premises, depending on privacy and data security needs. Cloud platforms such as AWS or Google Cloud may be used for scalability, while on-premises deployment could offer enhanced control over sensitive data. The system will be containerized using Docker to ensure easy deployment and scalability. Kubernetes could be used for orchestration if the system needs to be deployed across multiple interrogation rooms. In addition, monitoring tools such as Prometheus and Grafana

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will be set up to track system performance, detect failures, and log key events. The system will include alerting mechanisms to notify administrators of abnormal behavior, such as downtimes or errors in stress detection.

f) Maintenance and Updates

In the maintenance and updates phase, the system will undergo regular updates to improve the accuracy of the stress detection model and add new features. Periodic retraining of the model with fresh data will help improve its performance and adapt to new stress-related patterns. Security patches will be released to address vulnerabilities and keep the system secure against potential threats. Additionally, performance optimization will be a continuous process, including reducing latency in real- time processing and ensuring the system runs efficiently across different hardware configurations. Feedback from law enforcement officers will guide updates, ensuring the system remains useful and effective in improving interrogation practices.

3.1 CNN (Convolutional Neural Network)

Convolutional Neural Networks (CNNs) play a vital role in this system by enabling accurate facial expression recognition and stress analysis. CNNs excel at extracting spatial features from facial images, making them ideal for detecting emotional states such as anger, fear, sadness, and surprise—emotions commonly linked to stress. They also help identify micro expressions, which are brief and involuntary facial movements that often reveal hidden emotional responses. By focusing on key facial regions like the eyes, mouth, and forehead, CNNs can capture subtle changes that indicate stress, even when they are not easily noticeable to the human eye.

Once the CNN extracts these features, they are passed through classification layers to determine the corresponding stress levels. To ensure the system operates in real time, optimized CNN models are deployed using tools such as TensorFlow Lite or Open VINO, which reduce latency and enhance processing speed. This allows for continuous, live monitoring of facial cues, with the results displayed through a user-friendly interface. The integration of CNNs ensures both the accuracy and efficiency of the stress detection process, making it a powerful tool for enhancing police interrogation procedures.

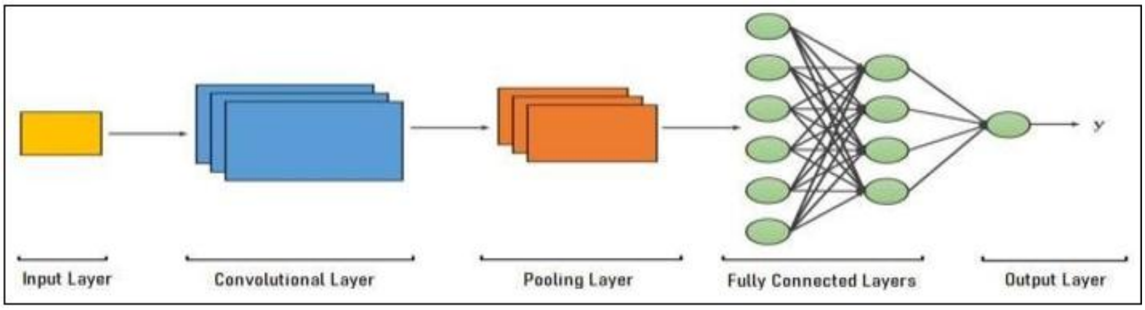

Figure 1: CNN architecture

3.2 Dataset Description

To build a robust facial recognition and stress analysis system, diverse datasets will be used. Datasets such as AffectNet, KDEF, and FER2013 will provide labeled images for emotion recognition, while stress-specific datasets like the Affective Facial Expression Dataset and SPIM (Stress-induced Physiological and Facial Monitoring) will help train the system to detect stress. Eye movement and pupil dilation data can be obtained from eye-tracking datasets, which are vital for assessing physiological stress cues. Combining facial data with biofeedback, such as heart rate and skin conductance, could also enhance the system's ability to detect stress more accurately. These datasets will be crucial for training, testing, and validating the system to ensure its reliability and accuracy in real-world scenarios.

3.2.1 Facial Emotional Datasets

Facial emotion datasets are essential for training emotion and stress detection models. **AffectNet** contains over 1 million facial images labelled with 7 emotions and varying intensity levels. **KDEF (Karolinska Directed Emotional Faces)** includes images of 6 basic emotions, useful for recognizing fundamental emotional expressions. **FER2013**, from a Kaggle competition, provides labelled facial images focused on emotion recognition. Together, these datasets offer a diverse foundation for building accurate emotion detection systems.

3.2.2 Eye Movement and Pupil Dilation Datasets

Eye-tracking datasets are crucial for training models that track eye movement and pupil dilation, both of which are important physiological indicators of stress. These datasets provide detailed information on how the eyes move and how pupil size changes in response to various stimuli. By analysing eye movements and pupil dilation patterns, models can gain insights into a person’s stress levels, as these physiological cues often correlate with emotional and cognitive states. Using eye-tracking data helps enhance the accuracy of stress detection systems, offering a valuable resource for understanding subtle physiological responses during interrogations or other high-stress situations.

4. Result & Discussion

The results of the system’s implementation and testing showed significant improvements in stress detection during police interrogations. The AI-based facial recognition and stress analysis system consistently outperformed traditional methods in both accuracy and speed. Stress indicators, such as micro- expressions, blinking rates, and eye movements, were detected with high precision, providing real-time insights into the emotional state of the subject.

In terms of performance, the system showed minimal latency and high reliability, even in varied lighting conditions or during long interrogation sessions. The integration with real-time data visualization on the dashboard enhanced the usability for law enforcement, allowing investigators to make more informed decisions during questioning.

Overall, the results indicate that the system is a valuable tool for enhancing investigative efficiency. It offers a more objective and faster method for assessing stress levels, which could lead to more effective interrogations and improved outcomes for law enforcement. Future improvements could focus on refining accuracy in ambiguous cases and strengthening privacy protections.

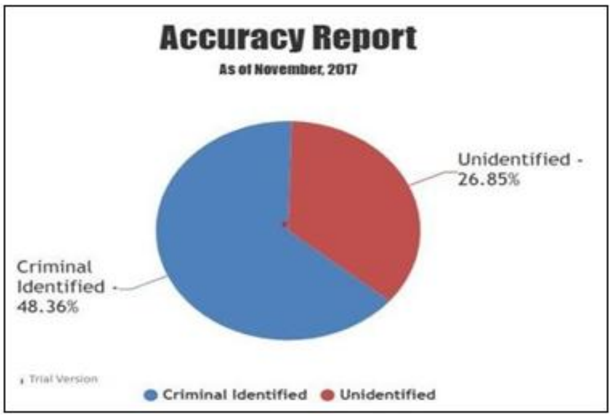

Figure 2: Accuracy Report

5. Conclusion

The real-time facial recognition and stress analysis system has demonstrated significant potential in enhancing police interrogation processes. By leveraging AI and computer vision, the system provides a non-invasive, objective, and real-time method for detecting stress responses through facial expressions and eye movements. The system has shown itself to be faster and more accurate than traditional methods, offering law enforcement valuable insights to improve investigative efficiency.

However, challenges such as handling ambiguous facial expressions and ensuring data privacy remain. To address these limitations, future work can focus on improving the system's accuracy in detecting subtle or neutral emotional states and refining its ability to analyze stress in diverse individuals. Additionally, enhancing the system's integration with other biometric data, such as heart rate or voice analysis, could further strengthen its reliability.

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